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Measuring Climatic and Hydrological Effects on Cereal crop Production in Bangladesh using Multiple Regression and Measuring Efficiency using Stochastic Frontier Model

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Abstract

The objective of this study is to develop a Multiple Regression model to measure the climatic and hydrological effects on cereal crop productions in Bangladesh and Stochastic Frontier model for measuring the production efficiency due to climate and hydrology. The month October, November, December, January and February are taken as "dry season" and March, April, May, June, July, August, September as a "summer season" considering the weather and climatic conditions of Bangladesh. From Multiple Regression model, it is found that the Multiple R-squared for maize, barley and wheat production model are 0.9447, 0.8995 and 0.7674 respectively, which are implied to a good model to measure the climatic and hydrological effects on cereal production; and Global test implies that these models are valid linear model. Again, from Stochastic Frontier model, it is found that there is a huge opportunity to increase barley and maize production; and wheat achieves maximum production due to climates and Hydrology in the Bangladesh.

Keywords: Cereal Production, Multiple Regression Model, Efficiency, Stochastic Frontier Model.

1. Introduction

Bangladesh has a large agrarian base country with 76 percent of total population is living in the rural areas and 90 percent of the rural population directly related with agriculture. Agriculture is the single largest producing sector of the economy since it comprises about 18.6% (data released on November, 2010) of the country's GDP and employs around 45% of the total labor force. Considering the climatic conditions Wheat, Maize, Barley, etc. are the major cereal crops in Bangladesh. The value for Cereal production (metric tons) in Bangladesh was 52,642,470 as of 2011.

Maize is a versatile crop and is more nutritious than rice in terms of protein, phosphorus, fat content and also in trace elements like magnesium, potassium and sulphur. It has an insignificant coverage of only 0.2 per cent of rice and three per cent of wheat acreage. With the introduction of high yielding seeds, its area and production have been expanding fast and it reached the level of 65,000 tons in 1997/98 from cultivation of 15,000 hectares of land. Among different districts of the country, Dinajpur, Rangpur, Bogra, Kushtia, Chuadanga and Dhaka are observed to be more progressive in maize cultivation.

Barley is a supplementary cereal crop after maize, wheat and rice in the world and third important cereal after rice and wheat in Bangladesh (FAO 1993-2002). Crop like barley requires far less water and can be cultivated in areas where irrigation water is less easily obtainable. The production of barley is gradually decreasing in Bangladesh (FAO 1993-2002). There are many reasons behind this decrease in production. In Bangladesh, farmers cultivate crops without considering proper sowing time. The actual cause of low yield is due to the effect of shorter growing period in the vegetative phase and steep rise in temperature at the grain filling stage (Nass et al. 1975). So, time of sowing of barley is a major limiting factor in Bangladesh. Early November is usually dry, warm and rich in soil moisture but the temperature decreases sharply to the lowest level in early January when the crop is in the vegetative stage. The reproductive phase commences when the temperature starts rising and water shortage occurs in the soil profile at the later part of the season

Wheat is not a traditional crop in Bangladesh, and in the late 1980s little was consumed in rural areas. During the 1960s and early 1970s, however, it was the only commodity for which local consumption increased because external food aid was most often provided in the form of wheat. Wheat also accounts for the great bulk of imported food grains, exceeding 1 million tons annually and going higher than 1.8 million tons in following year 1984, 1985, and 1987. The great bulk of the imported wheat is financed under aid programs of the United States, the European Economic Community, and the World Food Program.

Climate change in Bangladesh is an extremely crucial issue and according to National Geographic, Bangladesh ranks first as the nation most vulnerable to the impacts of climate change in the coming decades**.** Climate change and agriculture are interrelated processes, both of which take place on a global scale. Global warming is projected to have significant impacts on conditions affecting agriculture, including temperature, carbon dioxide, glacial run-off, precipitation and the interaction of these elements. These conditions determine the carrying capacity of the biosphere to produce enough food for the human population and domesticated animals. The overall effect of climate change on agriculture will depend on the balance of these effects. Assessment of the effects of global climate changes on agriculture might help to properly anticipate and adapt farming to maximize agricultural production.

2. Review of Literature

A lots of work has done about the effects of climatic and hydrological variable on agricultural production such as Mohammed Amir Hamjah (2014) has conducted an analysis to measure the climatic effects on Cotton and Tea production in Bangladesh by using Multiple Regression Model and here he also measure the production efficiency due to climates using Stochastic Frontier Model. Richard M. Adams, Brian H. Hurd, Stephanie Lenhart and Leary (Inter-Research, 1998) have conduct a study, which reviews the extant literature on these physical and economic effects and interprets this in terms of common themes or findings. Shafiqur Rahman (September, 2008) conduct an analysis by which he has shown the significant effects of temperature on agricultural production by using regression and correlation analysis. Hag Hamad Abdelaziz, Adam Abdelrahman, Abdalla and Mohmmed Alameen Abdellatif (2010) have shown that shed light on the main constraints of crop production in the traditional rainfed sector in Umkdada district, North Darfur State (Sudan). The study used descriptive statistics and regression for data analysis. The results of regression analysis revealed that the crops produced in season 2006 were significantly affected by some factors. Rahman, Mia and Bhuiyan (2012) has conducted in the year 2008-2009 to estimate the farm-size-specific productivity and technical efficiency fall rice crops. Farm-size-specific technical efficiency scores were estimated using stochastic production frontiers. There were wide of variations of productivity among farms, where large farms exhibited the highest productivity. The lowest net return or the highest cost of production was accrued from both the highest wage rate and highest amount of labour used in medium farms. Muhammad Fauzi Makki, Yudi Ferrianta, Rifiana and Suslinawati (2012) has conducted a study in Indonesia to evaluate the impact of climate change on productivity and technical efficiency paddy farms in tidal swamp land. The analysis showed Impact on productivity have not good because negative. Paulo Dutra Constantin and Diogenes Leiva Martin (2009) was conducted a study to apply a Cobb-Douglas Translog Stochastic Production Function and Data Envelopment Analysis in order to estimate inefficiencies over time as well as respective TFP (Total Factor Productivity) sources for main Brazilian grain crops - namely, rice, beans, maize, soybeans and wheat - throughout the most recent data available comprising the period 2001-2006.

3. Objective of the study

The main objective of this study is to develop a Multiple Regression model to measure the climatic and hydrological effects on cereal crop productions in Bangladesh and Stochastic Frontier model for measuring the production efficiency due to climate and hydrology. The specific objective of this study is to develop an individual Multiple Regression model to measure the climatic and hydrological effects on specific cereal crops named as Wheat, Barley and Maize productions and Stochastic Frontier model of Cobb-Douglas type for measuring the productions efficiency due to climates and hydrology covering the whole Bangladesh.

4. Data source and Data manipulations

The climatic data sets are available from the Bangladesh Government’s authorized websites www.barc.gov.bd. The crop data sets are also available from Bangladesh Agricultural Ministry’s websites named as www.moa.gov.bd. These data set are available from the year1972 to 2006. Climatic and hydrological information was in the original form such that it is arranged in the monthly average information corresponding to the years from 1972 to 2006 according to the 30 climatic stations. The name of these stations are Dinajpur, Rangpur, Rajshahi, Bogra, Mymensingh, Sylhet, Srimangal, Ishurdi, Dhaka, Comilla, Chandpur, Josser, Faridpur, Madaripur, Khulna, Satkhira, Barisal, Bhola, Feni, MaijdeeCourt, Hatiya, Sitakunda, Sandwip, Chittagong, Kutubdia, Cox's Bazar, Teknaf, Rangamati, Patuakhali, Khepupara, Tangail, and Mongla. We take the month October, November, December, January and February as a “dry season” and March, April, May, June, July, August, September as a “summer season” considering the weather and climatic conditions of Bangladesh. Finally, we take average seasonal climatic information of 30 climatic station corresponding to the year from 1972 to 2006. We take the average of 30 climatic area because of focusing the overall country’s situation and overall model fitting for whole Bangladesh.

5. Climatic and Hydrological Variables Used in This Study

sun.sum = Sunshine of the Summer Season, **sun.dry** = Sunshine of the Dry Season , **clo.sum** = Cloud Coverage of the Summer Season, **clo.dry** = Cloud Coverage of the Dry Season, **max.tem.dry** = Maximum Temperature of the Dry Season, **max.tem.sum** = Maximum Temperature of the Summer Season, **min.tem.dry** = Minimum Temperature of the Dry Season, **min.tem.sum** = Minimum Temperature of the Summer Season, **rain.dry**= Ammount of Rainfall of the Dry Season, **rain.sum** = Amount Rainfall of the Summer Season, **rh.dry** = Relative Humidity of the Dry Season, **rh.sum**= Relative Humidity of the Summer Season, **wind.dry** = Wind Speed of the Dry Season and **wind.sum** = Wind Speed of The Summer Season.

6. Used Software

This analysis has completely done by statistical programming based open source Software named as **R** with the version **2.15.1.** The additional library packages used for analysis is **lmtest, gvlma, car, frontier, etc.**

7. Methodology

7.1. Classical Linear Multiple Regression Model

The multiple classical linear regression model is given by

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} \dots \dots \dots . \beta_q X_{qi} + \varepsilon_i \text{ , } i = 1,2,3, \dots , N \tag{1}$$

Here, Y = Dependent variable, X_i's are independent variables, ε = stochastic error term, and β_0, β_1, β_2, … B_q are the model's parameter which are to be estimated.

There are five critical assumptions relating to Classical Linear Multiple Regression Model. These assumptions required to show that the estimation technique, Ordinary Least Squares (OLS), has a number of desirable properties, and also so that the hypothesis tests regarding the coefficient estimates could validly be conducted. These assumptions are (1) E (ε i) = 0 , The errors have zero mean, (2) Var (εi) = $\sigma^2 < \infty$, The values variance of the error is constant and have finite over all values of x_i, (3) Cov (ε i , ε j) = 0, The errors are statistically independent of one another, (4) Cov (ε ,i x i) = 0, There is no relationship between the error and the corresponding x, (5) $\varepsilon_i \sim N(0, \sigma^2)$, ε_i is normally distributed.

7.1.1. Shapiro–Wilk Normality Test

In statistics, the Shapiro–Wilk test tests the null hypothesis that a sample x1, ..., xn come from a normally distributed population. It was published in 1965 by Samuel Shapiro and Martin Wilk. The test statistic is:

$$w = \frac{(\sum_1^n a_i x_{(i)})^2}{\sum_1^n (x_i - \bar{x})^2} \dots \dots . \dots (2)$$

Where, $x_{(i)}$ (with parentheses enclosing the subscript index i) is the ith order statistic, i.e., the ith-smallest number in the sample; $\bar{x}$ is the sample mean; the constants, $a_{(i)}$ are given by (3)

$$(a_1, a_2 , \quad a_n) = \frac{m^T V^{-1}}{(m^T V^{-1} V^{-1} m)^2} \dots \dots . \dots (3)$$

Where, $m = (m_1, m_2, \dots, m_n)^T$ and m_1, …., m_n are the expected values of the order statistics of independent and identically distributed random variables sampled from the standard normal distribution, and **V** is the covariance matrix of those order statistics. The user may reject the null hypothesis if **W** is too small.

7.1.2. Box-Ljung Test

Ljung-Box (Box and Ljung, 1978) test can be used to check autocorrelation among the residuals. If a model fit well, the residuals should not be correlated and the correlation should be small. In this case the null hypothesis is $H_0 : \rho_1(e) = \rho_2(e) = \ldots\ldots = \rho_k(e) = 0$ is tested with the Box-Ljung statistic $Q^* = N(N+1)\sum_{i=1}^{k}(N-k)\ \rho_k^2(e)$
Where, N is the no of observation used to estimate the model. This statistic Q* approximately follows the chi-square distribution with (k-q) df, where q is the no of parameter should be estimated in the model. If Q* is large (significantly large from zero), it is said that the residuals autocorrelation are as a set are significantly different from zero and random shocks of estimated model are probably auto-correlated. So one should then consider reformulating the model.

7.1.3. Studentized Breusch-Pagan test

A formal test for detecting heteroscedasticity is Studentized Breusch-Pagan test (Breusch and Pagan, 1979) can be explained as for a given model, $Y = X^T\beta + €$

With $t = 1, 2, 3, \ldots, n$ and $X^T = [X_{1t}, X_{2t}, \ldots\ X_{kt}]$

We assume that heteroscedasticity takes the form: E (ut) = 0 for all t and $\boldsymbol{\sigma^2} = E(ut^2) = h(Z_t^T, \alpha)$, where $Z^T = [Z_{1t}, Z_{2t,\ldots\ldots\ldots}\ Z_{pt}]$ and $\alpha = [\alpha_1, \alpha_2, \ldots; \alpha_p]$ is a vector of unknown coecients and h(.) is some not specied function that must take only positive values. The null hypothesis (homoscedasticity) is then: $H_0 = \alpha_2 = \alpha_2 = \ldots = \alpha_p = 0$. Under the null we have $\boldsymbol{\sigma^2_t} = h(\alpha_1)$ (constant). The restricted model under the null is estimated by OLS, assuming disturbances are normally distributed. If the null hypothesis accepted then the error variance is homoscedastic.

7.1.4. Global Test of Validity Checking for a Linear Model

An easy-to-implement global procedure for testing the four assumptions of the linear model is proposed. The test can be viewed as a **Neyman smooth test** (1937) and it only relies on the standardized residual vector. If the global procedure indicates a violation of at least one of the assumptions, the components of the global test statistic can be utilized to gain insights into which assumptions have been violated. The procedure can also be used in conjunction with associated deletion statistics to detect unusual observations.
This distributional assumption, together with the linear link specification in are enumerated as four distinct assumptions:
(A1) (*Linearity*) $\mathbf{E}\{Y_i|\mathbf{X}\} = \mathbf{x}_i\beta$,where $\mathbf{x}_i$ is the *i*th row of **X**;
(A2) (*Homoscedasticity*) $\mathbf{Var}\{Y_i|\mathbf{X}\} = \sigma^2$, $i = 1,2,\ldots,n$;
(A3) (*Uncorrelatedness*) $\mathbf{Cov}\{Y_i,Y_j|\mathbf{X}\} = 0, (i \neq j)$; and
(A4) (*Normality*) $(Y_1,Y_2,\ldots,Y_n)|\mathbf{X}$ have a multivariate normal distribution.

Assumptions (A3) and (A4) imply that, given **X**, Y_i, $i = 1, 2, \ldots, n$ are independent normal random variables. Without loss of generality, we assume that **X** is of full rank with $n > p$, so rank(**X**) = p. Under (A1)–(A4),the maximum likelihood (ML) estimators of β and σ^2 are given, respectively, by
$\mathbf{b} = \beta\hat{} = (\mathbf{XtX})^{-1}\,\mathbf{XtY}$ and $s^2 = \sigma^2 = \ln\mathbf{Y}t(\mathbf{I}-\mathbf{P}[\mathbf{X}])Y$;
Assessment of whether assumptions (A1)–(A4) are satisfied, based on the data (**Y**, **X**), has received considerable attention. Assessment procedures typically involve the standardized residuals **R**, herein defined according to

$$\boldsymbol{R_i} = \frac{(\boldsymbol{Y_i} - \boldsymbol{\hat{Y}})}{\boldsymbol{s}}$$

Where, $\hat{Y}_i$ is the fitted value of Y_i
Formal significance tests for (A1)–(A4) involve testing the null hypothesis (H_0) versus the alternative hypothesis (H_1), where
H_0 : Assumptions (A1)−(A4) all hold
H_1 : At least one of (A1)−(A4) does not hold.
The first and second components for the test is given by

$$S_1 = \left\{\frac{1}{\sqrt[2]{6n}}\sum_{i=1}^{n} R^3{}_i\right\}^2$$

$$S_2 = \left\{\frac{1}{\sqrt[2]{24n}} \sum_{i=1}^{n} (R^4{}_i - 3)\right\}^2$$

The third component for the test is given by

$$S_3 = \frac{\{\frac{1}{\sqrt{n}} \sum_{i=1}^{n} (Y_i - \hat{Y})^2 R_i\}^2}{(\widehat{\Omega} - b^t \sum_x b - \Gamma \widehat{\sum_x}^{-1} \Gamma)}$$

Where, $\widehat{\Omega} = \frac{1}{n} \sum_{i=1}^{n} (Y_i - \hat{Y})^4$ and $\widehat{\sum_x} = \sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})$

$$\Gamma = \frac{1}{n} \sum_{i=1}^{n} \left(Y_i - \hat{Y}\right)^2 (X_i - \bar{X})$$

The Fourth component for the test is given by(the fourth component statistic requires a user-supplied n × 1 vector V, which by default is set to be the time sequence V = (1, 2, . . . , n)^t.)

$$S_4 = \frac{1}{\sqrt{2\,\hat{\sigma}^2\, n}} \sum_1^n (V_i - \bar{V})({R_i}^2 - 1)$$

Where $\hat{\sigma}^2 = \frac{1}{n} \sum_1^n (V_i - \bar{V})^2$

The global test statistics is given by $G^2 = S_1 + S_2 + S_3 + S_4$

Now reject H_0, if $G^2 > G^2{}_{\alpha,4}$

7.2. Stochastic Frontier Model

7.2.1. The Production Frontier: Theoretical Framework

The standard definition of a production function is that it gives the maximum possible output for a given set of inputs, the production function therefore defines a boundary or a frontier. All the production units on the frontier will be fully efficient. Efficiency can be of two kinds: technical and allocative. Technical efficiency is defined either as producing the maximum level of output given inputs or as using the minimum level of inputs given output Allocative efficiency occurs when the marginal rate of substitution between any of the inputs equals the corresponding input price ratio. If this equality is not satisfied, it means that the country is not using its inputs in the optimal productions. A production frontier model can be written as:

$$y_i = f(x_i;\ \beta)\, TE_i \tag{4}$$

Where, y_i is the output of producer i (i = 1, 2,…, N); x_i is a vector of M inputs used by producer i; $f(x_i;\ \beta)$ is the production frontier and β is a vector of technology parameters to be estimated. Let TE_i be the technical efficiency of producer i,

$$TE_i = \frac{y_i}{f(x_i;\ \beta)} \tag{5}$$

In the case, $TE_i = 1$, y_i achieves its maximum feasible output of $f(x_i;\ \beta)$. If $TE_i < 1$, it measures technical inefficiency in the sense that observed output is below the maximum feasible output. The production frontier $f(x_i;\ \beta)$ is deterministic.We have to specify the stochastic production frontier

$$y_i = f(x_i;\ \beta) \exp(v_i)\, TE_i \tag{6}$$

Where, $f(x_i;\ \beta) \exp(v_i)$ is the stochastic frontier, which consists of a deterministic part $f(x_i;\ \beta)$ common to all producers and a producer-specific part which $\exp(v_i)$ captures the effect of the random shocks to each producer TE_i can be computed for Stocahastic Fromntier production of ith producer

$$TE_i = \frac{y_i}{f(x_i;\ \beta) \exp(v_i)} \tag{7}$$

7.2.2. Stochastic Frontier Productions Function

The econometric approach to estimate frontier models uses a parametric representation of technology along with a two-part composed error term. Under the assumption that is of $f(x_i;\ \beta)$ is of Cobb-Douglas type, the stochastic frontier model in equation (7) can be written as

$$Y_i = \alpha + \beta X_i + \varepsilon_i \tag{8}$$

Where, ε_i is an error term with $\varepsilon_i = v_i - u_i$

The economic logic behind this specification is that the production process is subject to two economically distinguishable random disturbances: statistical noise represented by v_i and technical inefficiency represented by u_i

There are some assumptions necessary on the characteristics of these components. The errors v_i are assumed to have a symmetric distribution, in particular, they are independently and identically distributed as N (0, σ_v^2) . The component u_i is assumed to be distributed independently of v_i and to satisfy $u_i \geq 0$ (e.g. it follows a one-sided normal distribution N^+ (0, σ_v^2). The non-negativity of the technical inefficiency term reflects the fact that if $u_i > 0$ the country will not produce at the maximum attainable level. Any deviation below the frontier is the result of factors partly under the production unit's control, but the frontier itself can randomly vary across firms, or over time for the same production unit. This last consideration allows the assertion that the frontier is stochastic, with a random disturbance v_i being positive or negative depending on favorable or unfavorable external events.

It is important to note that given the non-negativity assumption on the efficiency term, its distribution is non-normal and therefore the total error term is asymmetric and non-normal. This implies that the least squares estimator is inefficient. Assuming that v_i and u_i are distributed independently of x_i, estimation of (8) by OLS provides consistent estimators of all parameters but the intercept, since $E(\varepsilon_i) = -E(u_i) \leq 0$. Moreover, OLS does not provide an estimate of producer-specific technical efficiency. However, it can be used to perform a simple test based on the skewness of empirical distribution of the estimated residuals. Schmidt and Lin (1984) propose the test statistic

$$b^{1/2} = \frac{m_3}{m_2^{3/2}} \tag{9}$$

Where, m_2 and m_3 are the second and the third moments of the empirical distribution of the residuals. Since v_i is symmetrically distributed, m_3 is simply the third moment of the distribution of u_i.
The case $m_3 < 0$ implies that OLS residuals are negatively skewed, and that there is evidence of technical inefficiency. In fact, if $u_i > 0$ then $\varepsilon_i = v_i - u_i$ is negatively skewed. The positive skewness in the OLS residuals, i.e. $m3 > 0$, suggests that the model is mis-specified. Coelli (1995) proposed an alternative test statistic

$$b^{1/2} = \frac{m_3}{(6m_2^3/N)^{1/2}} \tag{10}$$

Where, N is equal to the number of observations. Under the null hypothesis of zero skewness in the OLS residuals, $m_3=0$, the third moment of OLS residuals is asymptotically distributed as a normal random variable with mean zero and variance $6m_2^3/N$. This implies that the test statistic (10) is asymptotically distributed as a standard normal random variable N (0,1).

Coelli (1995) presents Monte Carlo experiments where these tests have the correct size and good power. The asymmetry of the distribution of the error term is a central feature of the model. The degree of asymmetry can be represented by the following parameter:

$$\lambda = \frac{{\sigma_u}^2}{{\sigma_v}^2} \tag{11}$$

The larger λ is, the more pronounced the asymmetry will be. On the other hand, if λ is equal to zero, then the symmetric error component dominates the one-side error component in the determination of ε_i. Therefore, the complete error term is explained by the random disturbance v_i, which follows a normal distribution. ε_i therefore has a normal distribution. To test the hypothesis that $\lambda = 0$, we can compute a Wald statistic or likelihood ratio test both based on the maximum likelihood estimator of λ Coelli (1995) tests as equivalent hypothesis $\gamma = 0$ against the alternative $\gamma > 0$, where

$$\gamma = \frac{{\sigma_u}^2}{{\sigma_u}^2 + {\sigma_v}^2} \tag{12}$$

A value of zero for the parameter γ indicates that the deviations from the frontier are entirely due to noise, while a value of one would indicate that all deviations are due to technical inefficiency. The Wald statistic is calculated as

$$W = \frac{\hat{\gamma}}{\widehat{\sigma_\gamma}} \tag{13}$$

Where, $\hat{\gamma}$ is maximum likelihood estimate of γ and $\widehat{\sigma_\gamma}$ is its estimated standard error. Under H_0: γ = 0 is true, the test statistic is asymptotically distributed as a standard normal random variable. However, given that γ cannot be negative, the test is performed as a one-sided test. The likelihood test statistic is

$$LR = -2[Log(L_0) - Log(L_1)] \tag{14}$$

Where, log (L_0) is the log-likelihood valued under the null hypothesis and log (L_1) is the log-likelihood value under the alternative. This test statistic is asymptotically distributed as chi-square random variable with degrees of freedom equal to the number of restrictions. Coelli (1995) notes that under the null hypothesis γ = 0, the statistic lies on the limit of the parameter space since γ cannot be less than zero. He therefore concludes that the likelihood ratio statistic will have an asymptotic distribution equal to a mixture of chi-square distributions ($\frac{1}{2}\chi_0^2 + \frac{1}{2}\chi_1^2$).

8. Results and Discussion

8.1. Multiple Regression Model for Barely Production

The parameter estimates of the fitted Multiple Regression model for measuring the climatic and hydrological effects on barley production is given in Table 1.

Table 1: Summary Statistics of the Barley Production Model

Coefficients	**Estimate**	**Std. Error**	**t-value**	**p-value**
(Intercept)	114.281506	105.836863	1.08	0.2931
sun.sum	-0.449277	2.605465	-0.172	0.8648
sun.dry	3.032924	1.457077	2.082	0.0504
clo.sum	-2.673104	3.491705	-0.766	0.4529
clo.dry	6.066597	3.522408	1.722	0.1004
max.tem.dry	3.551555	2.193777	1.619	0.1211
max.tem.sum	-4.551864	3.804378	-1.196	0.2455
min.tem.dry	-3.414099	2.400826	-1.422	0.1704
min.tem.sum	-0.944122	2.996169	-0.315	0.7559
rain.dry	-0.020194	0.026427	-0.764	0.4537
rain.sum	-0.002193	0.012529	-0.175	0.8628
rh.dry	1.113078	0.493317	2.256	0.0354
rh.sum	-1.26452	0.968682	-1.305	0.2066
wind.dry	-7.581394	6.900143	-1.099	0.2849
wind.sum	16.281258	3.176243	5.126	<0.0001

From Table 1, we observe that sun.dry, clo.dry, max.tem.dry, rh.dry and wind.sum have positive effects on barley production; and sun.sum, clo.sum, max.tem.sum, min.tem.dry, min.tem.sum, rain.dry, rain.sum, rh.sum and wind.dry have negative effects on barley production. Again, sun.dry, rh.dry and wind.sum have statistically significant effects on barley productions at 10% level of significance.

Again, from the fitted Multiple Regression model, Multiple R-squared is 0.9447, which implies that 94.47% variation can be explained by the predictor variables and Adjusted R-squared is 0.9061, which implies that 90.61% variation can be explained by the predictor variables after adjustments and from overall test, the Pr(|$F_{(14,}$

$_{20)}| \geq 12.78) < 0.001$ implies that all the variables are not eqully significant effects on barley productions at 5% level of significance.

Added Variable Plots for the barley production model are shown in the Figure 1

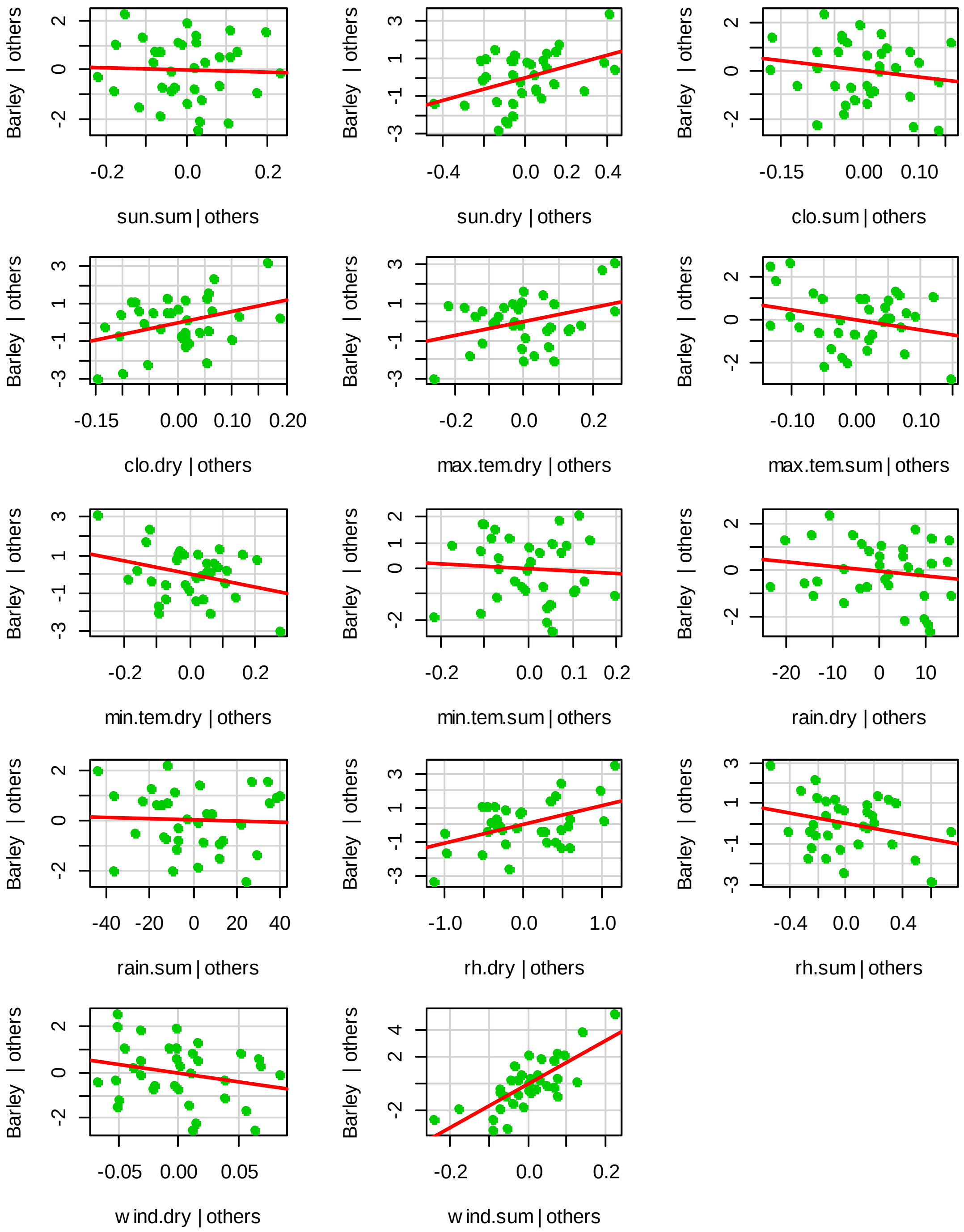

Figure 1: Added Variable Plots for Barley Production Model

From Figure 1, which displays the partial relationship between the response's (barley production) residuals and each of the predictor's residuals for barley production model. All plots are shown that they follow a staright line with non-zero slopes and there is no curvature relationship ammong the predictor's residuals and response residuals. That is why, it can be said that each of the variabls are added to the model maintaine a linear relationship. That is, this model is going to make a linear relationship between the response variable and the predictor variables to measure the climatic and hydrological effects on barley production in Bangladesh.

8.1.1. Residuals Diagnostics for Barley Production Model

Residuals Diaagonstics Plots for measuring the climatic and Hydrological effects on Maize production model are shown in the figure 2

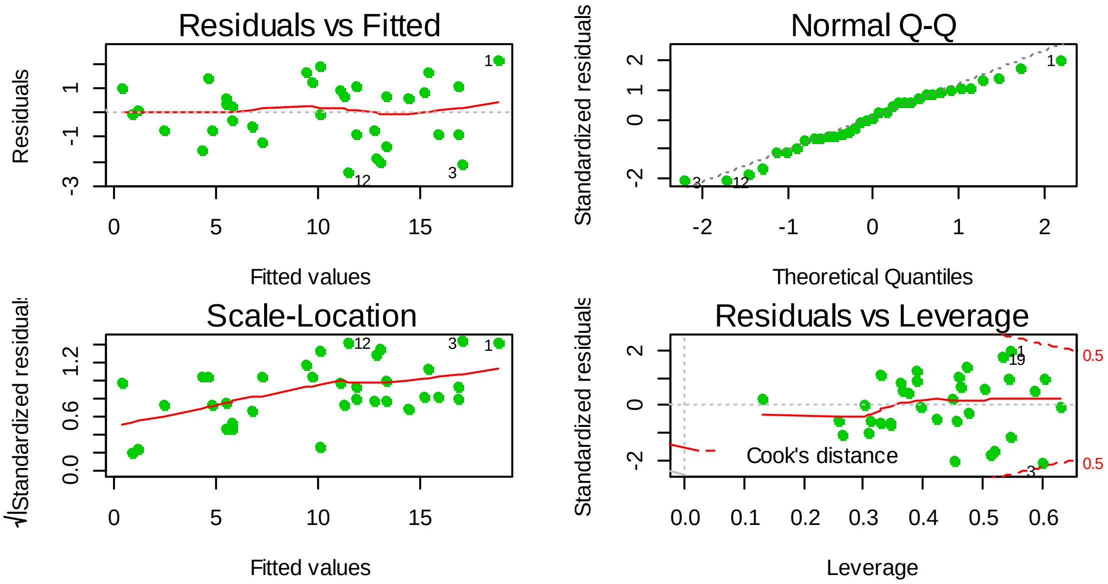

Figure 2: Residuals Diagnostics Plots for Barley Production Model

From Figure 2, we observe that,

1) all of the points lie around the horizontal line and they create horizontal band around the line and they do not show any other unusual pattern like funnel pattern, double bow pattern, non-linear pattern etc. which implies constant variance among the residuals of the barley production model (top-left).
2) almost all of the points try to create a horizontal band which indicates that residals have constant variance of the barley production model (bottom-left).
3) although there is a single leverage point, according to the cook's distance it is lied on the 50% Cook's interval of the leverage points, which has a little influence on the model estimation of the barley production model (bottom-right).
4) almost all of the points are very closed to Q-Q line or on the Q-Q line, which suggests that residuals are normally distributed of the barley production model (top-right).

To check different assumptions by using formal test for multiple regression model of barley production are shown in the Table 2

Table 2: Residuals Diagnostic Test for Assumptions Checking

Residuals Diagnostic	**Test Name**	**P-value**
Constant Variance test	Breusch-Pagan	$\Pr(\lvert\chi^2_{(14)}\rvert \geq 13.3215\ ) = 0.5014$
Auto-correlation test	Box-Ljung test	$\Pr(\lvert\chi^2_{(1)}\rvert \geq 0.1757) = 0.6751$
Normality Test	Shapiro-Wilk	$\Pr(\lvert\chi^2_{(35)}\rvert \geq 0.9707) = 0.4638$

From Table 2, it is clear that residuals of the fitted Multiple Regression model for barely production have constant variance, have no auto-correlation and they follow normal distribution at 5% level of significance which implies the fitted model's assumptions are very well managed to fit the linear Multiple Regression model for Barley production. These all test are made based on Chi-square test.

8.1.2. Global Validation Checking for Barley Production Model

Global model validation test is used here to check whether barley production model assumption is valid or not. The test is performed at 5% level of significance on 4 degrees of freedom. The results of the test are shown in the Table 3.

Table 3: Global Validation Checking for Barely Production Model			
Test Statistic	**Value**	**p-value**	**Decision**
Global Stat	4.1817	0.382	Assumptions acceptable.
Skewness	0.2117	0.6454	Assumptions acceptable.
Kurtosis	1.2688	0.26	Assumptions acceptable.
Heteroscedasticity	1.9099	0.167	Assumptions acceptable.

From Table 3, we observe that the p-value of Global stat is 0.382, which suggests that linearity of parameters, Homoscedasticity, Autocorrelation and Normality test are very well managed in the fitted model for barley production, that is , the fitted model is a valid model. Again, Skewness and Kurtosis of the fitted model are 0.2117 and 1.2688 respectively and their corresponding p-values are 0.6454 and 0.26, which suggest that the assumptions of the skewness and kurtosos are very well accepted to fit a linear model. At the same time, the heteroscedasticity assumptions is also accepted with the p-value of 0.167, which suggests homoscedasticity of variance. So, it can be said that the fitted model is the best fitted Multiple Linear Regression model for measuring the climatic and hydrological effects on barely production in Bangladesh.

Finally, from all of the formal and graphical test, assumptions of residuals like Homoscedasticity, Autocorrelation Normality are very well managed and model validation test "Global Tesst" also satisfied all of the assuptions for a linear model, that is, this fitted model is a valid model. Without any kind of loss of generality, it can be said that this fitted model is the best fitted model for measuring the climatic and hydrological effects on barely production in Bangladesh based on the sample data.

8.2. Stochastic Frontier Modeling for Barley Production

Parameter estimates of the fitted Stochastic Frontier Model of Trans-log Cobb-Douglas type for the barley production are given in the Table 4.

Table 4: Summary Statistics of the Frontier Model for Barley Production				
Coefficients	Estimate	Std. Error	z value	p-value
(Intercept)	70.771305	0.994508	71.1621	< 0.00001
sun.sum	-3.706872	0.607083	-6.106	< 0.00001
sun.dry	3.02289	0.729923	4.1414	0.0000345
clo.sum	-6.129199	0.938119	-6.5335	< 0.00001
clo.dry	1.290273	0.3726	3.4629	0.00053
max.tem.dry	8.916206	0.936015	9.5257	< 0.00001
max.tem.sum	-19.329548	0.905093	-21.3564	< 0.00001
min.tem.dry	-2.643447	0.961311	-2.7498	0.005963
min.tem.sum	-10.821376	0.911078	-11.8776	< 0.00001
rain.dry	0.131622	0.100286	1.3125	0.189363
rain.sum	-0.69206	0.288425	-2.3994	0.016422
rh.dry	5.436571	0.882818	6.1582	< 0.00001
rh.sum	-0.482251	0.89501	-0.5388	0.590009
wind.dry	-0.361985	0.393969	-0.9188	0.358192
wind.sum	3.404082	0.436393	7.8005	< 0.00001
sigmaSq	0.119942	0.021526	5.5719	< 0.00001
gamma	1	0.000551	1815.2904	< 0.00001

From the Table 4 of the summary statistics, it is clear that sun.sum, sun.dry, clo.sum, clo.dry, max.tem.dry, max.tem.sum, min.tem.dry, min.tem.sum, rain.sum, rh.dry and wind.sum have statistically significant effects on frontier barley production due to Climate and hydrology covering the whole county Bangladesh at 5% level of significance.

From the analysis, Average Technical Efficiency is 0.7885847. The highest value of the efficiency is 0.9992257, which occurs in the year 2001, that is, in the year 2001, Bangladesh achieves maximum barley production and the lowest is 0.3940353, that is, in the year 2001, Bangladesh achieves minimum barley production. These result indicate the majority of year are relatively not well in achieving maximum barley production. At the same time, according to the Coelli's test $H_0: \gamma = 0$, which gives the value of gamma is 1 and it's p-value for testing the hypothesis is < 0.00001, indicates highly significant which implies that all of the deviations arises due to technical inefficiency. It also means that there is a huge opportunity to increase barley production in the Bangladesh by increasing technology. Again, from the likelihood ratio test, it is found that the $\Pr(|\chi^2_{(1)}| \geq 14.069)$ <0.00001, which implies to reject the null hypothesis that there is no production inefficiency, that is, there exist inefficiency of barely production due to climate and hydrology in Banglaedsh.

8.3. Weighted Multiple Regression Model for Maize Production

We select Weighted Least Squares (WLS) methods because of avoiding the outlier and influential observations which have very bad effects on fitted model's properties by using Ordinary Least Square (OLS) method, where amounts of land area are used for maize production as a weights because the amount of land area increases or decreases in corresponding year's production proportionately. Also without Weighted Least Squares the assumption of Autocorrelation is violated. The parameter estimates of the fitted Weighted Multiple Regression model for measuring the climatic and hydrological effects on Maize production are given in Table 5.

Table 5: Summary Statistics of the Maize Production Model

Coefficients	**Estimate**	**Std. Error**	**t-value**	**p-value**
(Intercept)	-21135.3592	8366.935277	-2.526	0.0201
sun.sum	463.890819	189.831494	2.444	0.0239
sun.dry	-178.680153	96.688706	-1.848	0.0794
clo.sum	752.690618	257.457114	2.924	0.0084
clo.dry	-534.681324	237.542489	-2.251	0.0358
max.tem.dry	-225.990445	153.204731	-1.475	0.1558
max.tem.sum	513.640771	289.216838	1.776	0.0910
min.tem.dry	291.31071	187.212863	1.556	0.1354
min.tem.sum	8.010609	242.77573	0.033	0.974
rain.dry	-1.079978	1.938019	-0.557	0.5835
rain.sum	0.09504	1.130778	0.084	0.9339
rh.dry	-43.901523	37.892321	-1.159	0.2603
rh.sum	63.764516	69.592685	0.916	0.3705
wind.dry	1306.126881	569.877183	2.292	0.0329
wind.sum	-417.462628	330.554535	-1.263	0.2211

From Table 5, we observe that sun.sum, clo.sum, max.tem.dry, min.tem.sum, min.tem.dry, rain.sum, rh.sum and wind.dry have positive effects on maize production; and sun.dry, clo.dry, max.tem.dry, min.tem.dry, rain.dry, rh.dry and wind.sum have negative effects on maize production. Again, sun.sum, sun.dry, clo.sum, clo.dry, max.tem.sum and wind.dry have statistically significant effects on maize productions at 10% level of significance.

Again, from the fitted Multiple Regression model, Multiple R-squared is 0.8995, which implies that 89.95% variation can be explained by the regressors variable and Adjusted R-squared is 0.8291, which implies that 82.91% variation can be explained by the regressors variable after adjustments; and from overall test, $\Pr(|F_{(14, 20)}| \geq 12.78) < 0.0001$ implies that all the variables are not eqully significant effects on Maize production at 5% level of significance.

Added Variable Plots for the Maize production model are shown in the Figure 3

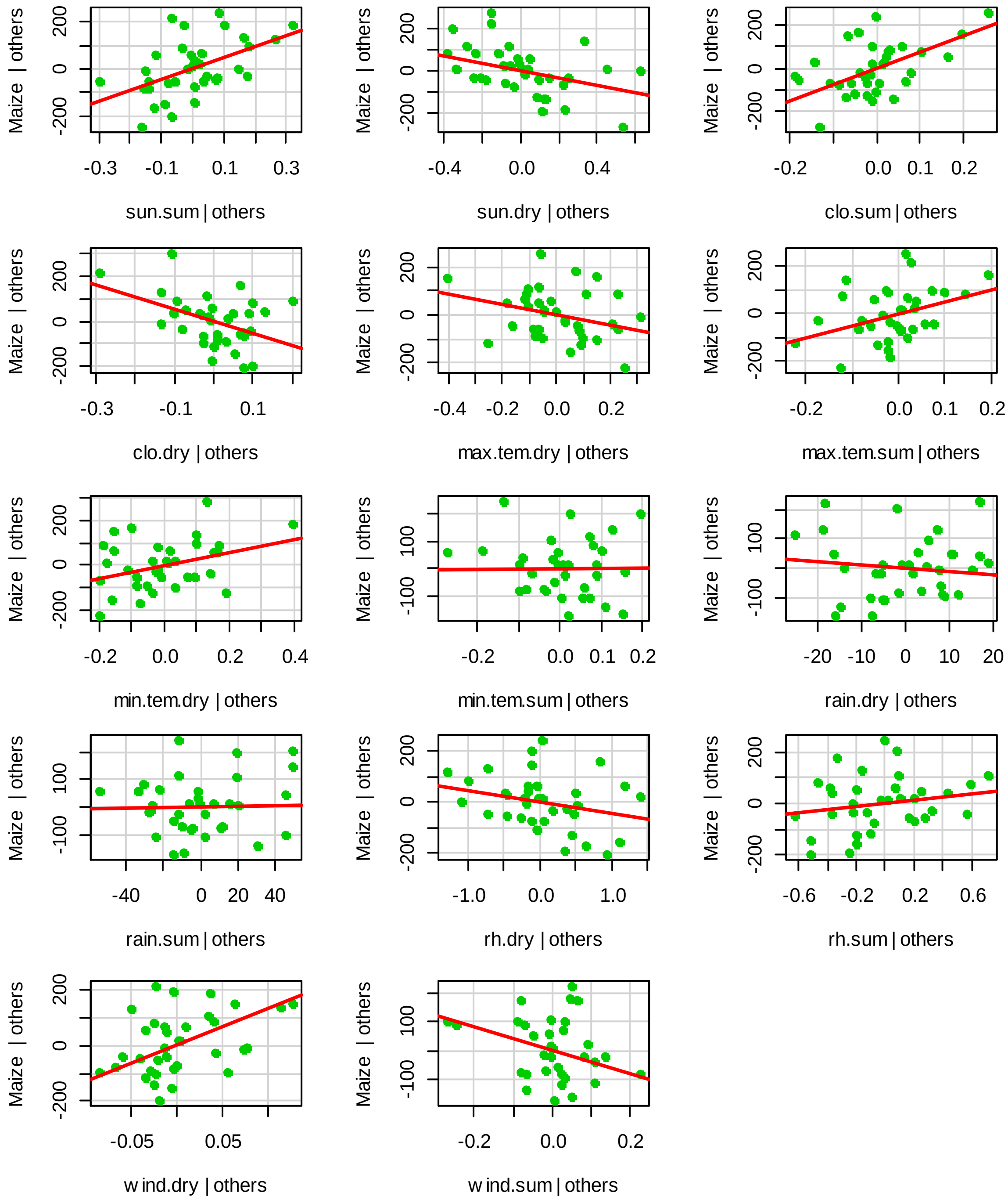

Figure 3: Added Variable Plots For Maize Production Model

From Figure 3, which displays the partial relationship between the response (Maize production) residuals and each of the predictor's residuals for maize production model. All plots are shown that they follow a staright line with non-zero slopes and there is no curvature relationship ammong the predictor's residuals and response residuals. That is why, it can be said that each of the predictor variabls are added to the model with maintaining a linear relationship. That is, this model is going to make a linear relationship between the response variable and the predictor variables to measure the climatic and hydrological effects on Maize production in Bangladesh.

8.3.1. Residuals Diagnostics for Maize Production Model

Residuals Diaagonstics Plots for measuring the climatic and hydrological effects on Maize production model are shown in the figure 4

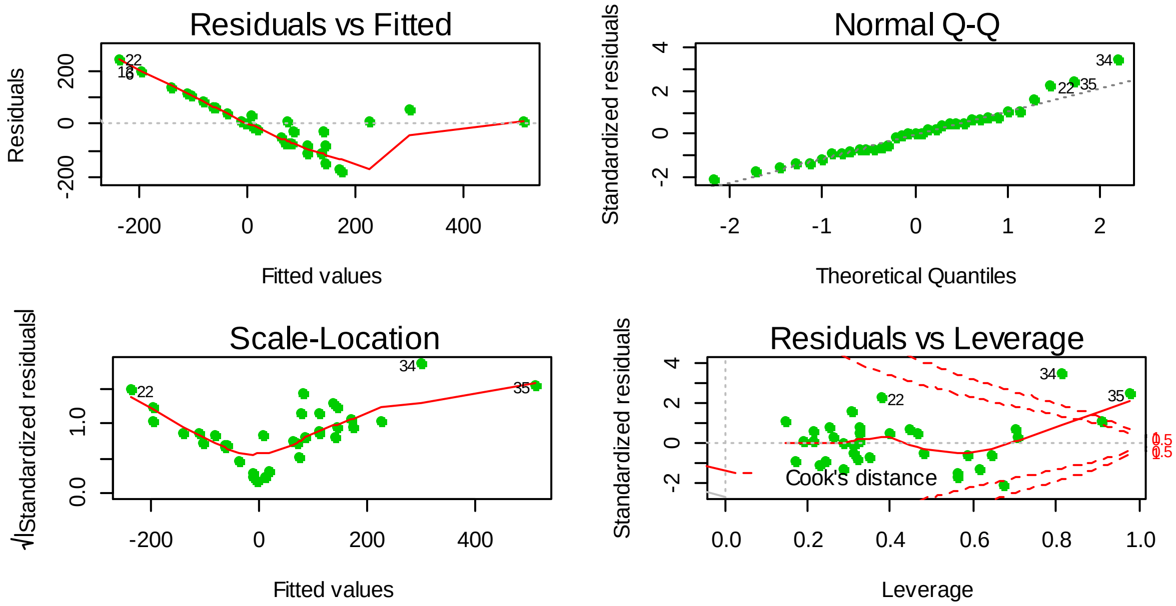

Figure 4: Residuals Diagonstics Plots for Maize Production Model

From Figure-4, we observe that,

1) all of the points are lied around the horizontal line, which implies constant variance among the residuals of the maize production model (top-left).
2) almost all of the points try to create a horizontal band which indicates that residals have constant variance of the maize production model (bottom-left).
3) although there are two leverage point, according to the cook's distance it is outside the 100% Cook's interval of the leverage points, which has huge influence on the model estimation of the maize production model (bottom-right).
4) almost all of the points are very closed to Q-Q line or on the Q-Q line, which suggests that residuals are normally distributed of the maize production model (top-right).

To check different assumptions by using formal test for Multiple Regression model of maize production are shown in the following Table 6

Table 6: Residuals Diagnostic test for Assumptions Checking

Residuals Diagnostic	**Test Name**	**P-value**
Constant Variance test	Breusch-Pagan	$\Pr(\lvert\chi^2_{(14)}\rvert \geq 14.7424) = 0.396$
Auto-correlation test	Box-Ljung test	$\Pr(\lvert\chi^2_{(1)}\rvert \geq 1.1861) = 0.2761$
Normality Test	Shapiro-Wilk	$\Pr(\lvert\chi^2_{(35)}\rvert \geq 0.9744) = 0.5738$

From Table 6, it is clear that residuals of the fitted Multiple Regression model for maize production have constant variance, have no auto-correlation and they follow normal distributions at 5% level of significance which implies the fitted model's assumptions are very well satisfied. These all test are made based on Chi-square test.

8.3.2. Global Validation Checking for Maize Production Model

Global model validation test is used to check whether maize production model assumption are valid or not. The test is performed at 5% level of significance on 4 degrees of freedom. The results from the test are shown in the Table 7.

Table 7: Global Validation Checking for Maize Production Model

Test Statistics	**Value**	**p-value**	**Decision**
Global Stat	4.18685	0.1601	Assumptions acceptable
Skewness	1.57306	0.20976	Assumptions acceptable.
Kurtosis	0.03497	0.85166	Assumptions acceptable.
Heteroscedasticity	1.67152	0.19606	Assumptions acceptable.

From Table 7, we observe that the p-value of Global stat is 0.1601, which suggests that linearity of parameters is sufficient to build the model; Homoscedasticity, Autocorrelation and Normality test are very well managed in the fitted model, that is, the fitted model is a valid model. Again, Skewness and Kurtosis of the fitted model are 1.57306 and 0.03497 respectively and their corresponding p-values are 0.20976 and 0.85166, which suggest that the assumptions of the skewness and kurtosos are very well accepted to fit a linear model. At the same time, the heteroscedasticity assumptions is also accepted with the p-value of 0.19606, which suggests homoscedasticity of variance. We can easily say that the fitted model is the best fitted Multiple Linear Regression model for measuring the climatic and hydrological effects on maize productions.

Finally, from all of the Graphical and formal test, assumptions of residuals like Homoscedasticity, Autocorrelation Normality are very well satisfied and model validation test “Global Tesst” also satisfied all of the assuptions of a linear model and the fitted model is a valid model. Without any kind of loss of generality, it can be said that this fitted model is the best fitted model for measuring the climatic effects on Maize productions based on the sample data.

8.4. Stochastic frontier modeling for Maize production

Parameter estimates of the fitted stochastic frontier model of Trans-log Cobb-Douglas type for the maize production are given in the Table 8.

Table 8: Summary statistics of the frontier model for Maize productions model

Coefficients	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-553.802431	0.995357	-556.3855	< 0.0001
sun.sum	5.307209	0.597334	8.8848	< 0.0001
sun.dry	-3.812858	0.800548	-4.7628	< 0.0001
clo.sum	10.325882	0.951977	10.8468	< 0.0001
clo.dry	-2.946261	0.49467	-5.956	< 0.0001
max.tem.dry	-26.994148	0.949217	-28.4383	< 0.0001
max.tem.sum	132.60646	0.889003	149.1631	< 0.0001
min.tem.dry	19.633982	0.944399	20.7899	< 0.0001
min.tem.sum	-23.7356	0.827602	-28.68	< 0.0001
rain.dry	0.032154	0.201133	0.1599	0.873
rain.sum	2.21742	0.560034	3.9594	< 0.0001
rh.dry	-22.191383	0.775405	-28.6191	< 0.0001
rh.sum	63.05824	0.916998	68.766	< 0.0001
wind.dry	0.750944	0.186418	4.0283	< 0.0001
wind.sum	-3.985393	0.672339	-5.9277	< 0.0001
sigmaSq	1.284608	0.089351	14.3771	< 0.0001
gamma	1	0.000003	351447.8619	< 0.0001

From the Table 8 of the summary statistics, it is clear that all except rain.dry have statistically significant effects on frontier maize production due to Climate and hydrology covering the whole Bangladesh at 5% level of significance.

From the analysis results, Average Technical Efficiency is 0.4854803. The highest value of the efficiency is 0.99937113, which occurs in the year 1993, that is, in the year 1993, Bangladesh achieves maximum maize production and the lowest is 0.04245025, which occurs in the year 2000, that is, in the year 2001, Bangladesh achieves minimum maize production. These result indicate the majority of year are relatively not well in achieving maximum maize production. Efficiency rate 48% gives sense that almost halve of the year can achieve maximum maize production. At the same time, according to the Coelli's test $H_0: \gamma = 0$, gives the value of gamma is 1 and it's p-value for testing the hypothesis is < 0.0001 indicates highly significant, which implies that all of the deviations arises due to technical inefficiency. It also means that there is a huge opportunity to increase maize production in the Bangladesh by increasing technology. Again, from the likelihood ratio test, it is found that the $\Pr(|\chi^2_{(1)}| \geq 10.937) = 0.00047$, which implies to reject the null hypothesis that there is no production inefficiency, that is, there exist inefficiency of the maize production in Bangladesh due to climate and hydrology.

8.5. Multiple Regression Modeling for Wheat Production

we try to fit the Multiple Regression model by using Box-Cox transformation to adjust the response variable ($\lambda = 0.5868179$) and avoid the autocorelation problem. The parameter estimates of the fitted Multiple Regression model for measuring the climatic and hydrological effects on Wheat production are given in Table 9.

From Table 9, we observe that clo.dry, max.tem.dry, min.tem.sum, and rh.sum have positive effects on maize production; and sun.sum, sun.dry, clo.sum, max.tem.sum, min.tem.dry, rain.dry, rain.sum, rh.dry, wind.dry and wind.sum have negative effects on wheat production. Again, sun.sum and clo.sum have statistically significant effects on wheat production at 10% level of significance.

Table 9: Summary Statistics of the Wheat Production Model

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	420.365765	839.388962	0.501	0.622
sun.sum	-42.865678	20.663864	-2.074	0.0512
sun.dry	-2.913319	11.556037	-0.252	0.8035
clo.sum	-49.328522	27.692606	-1.781	0.0901
clo.dry	16.244026	27.936114	0.581	0.5674
max.tem.dry	16.158861	17.398782	0.929	0.3641
max.tem.sum	-13.107477	30.172408	-0.434	0.6686
min.tem.dry	-14.862177	19.040878	-0.781	0.4442
min.tem.sum	12.754677	23.762522	0.537	0.5974
rain.dry	-0.011212	0.209588	-0.053	0.9579
rain.sum	-0.004457	0.099363	-0.045	0.9647
rh.dry	-0.377733	3.912482	-0.097	0.924
rh.sum	1.198523	7.68259	0.156	0.8776
wind.dry	-8.484746	54.724828	-0.155	0.8783
wind.sum	-24.026837	25.190686	-0.954	0.3516

Again, from the fitted Multiple Regression model, Multiple R-squared is 0.7674, which implies that 76.74% variation can be explained by the regressors variable and Adjusted R-squared is 0.6045, which implies that 60.45 % variation can be explained by the regressors variable after adjustments and from overall test, $\Pr(|F_{(14, 20)}| \geq 4.712) = 0.000902$ implies that all the variables are not eqully significant effects on Wheat productions at 5% level of significance.

Added Variable Plots for the wheat production model are shown in the Figure 5

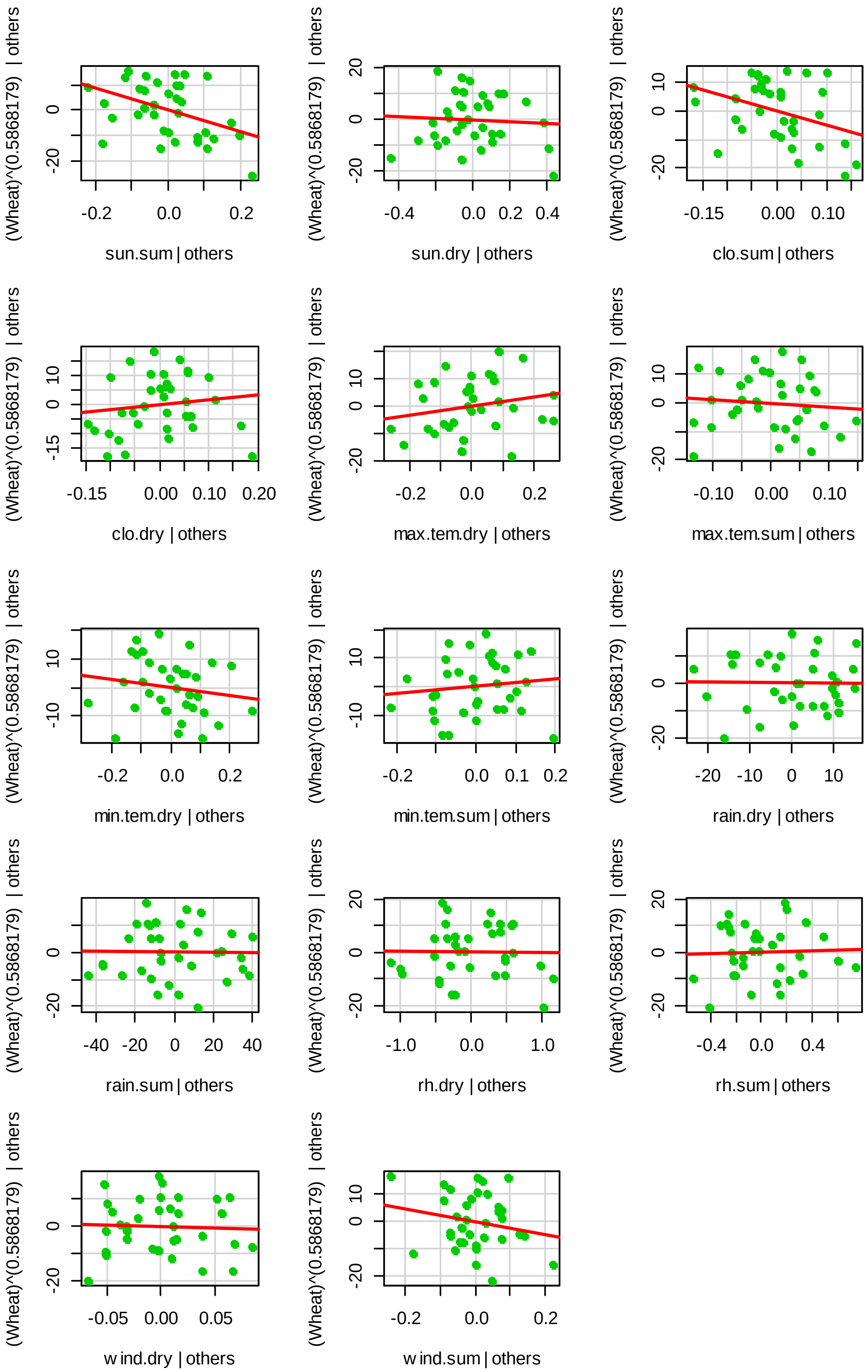

Figure 5: Added Variable Plots for Wheat Production Model

From Figure 5, which displays the partial relationship between the response (Wheat production) residuals and each of the predictor's residuals for wheat production model. All plots show that they follow a staright line with non-zero slopes and there is no curvature relationship ammong the predictor's residuals and response residuals. That is why, it can be said that each of the predictor variabls are added to the model with maintaining a linear relationship. That is, this model is going to make a linear relationship between the response variable and the predictor variables to measure the climatic and hydrological effects on Wheat production in Bangladesh.

8.5.1. Residuals Diagnostics for Wheat Production Model

Residuals Diaagonstics Plots for measuring the climatic and hydrological effects on Wheat production model are shown in the figure 6

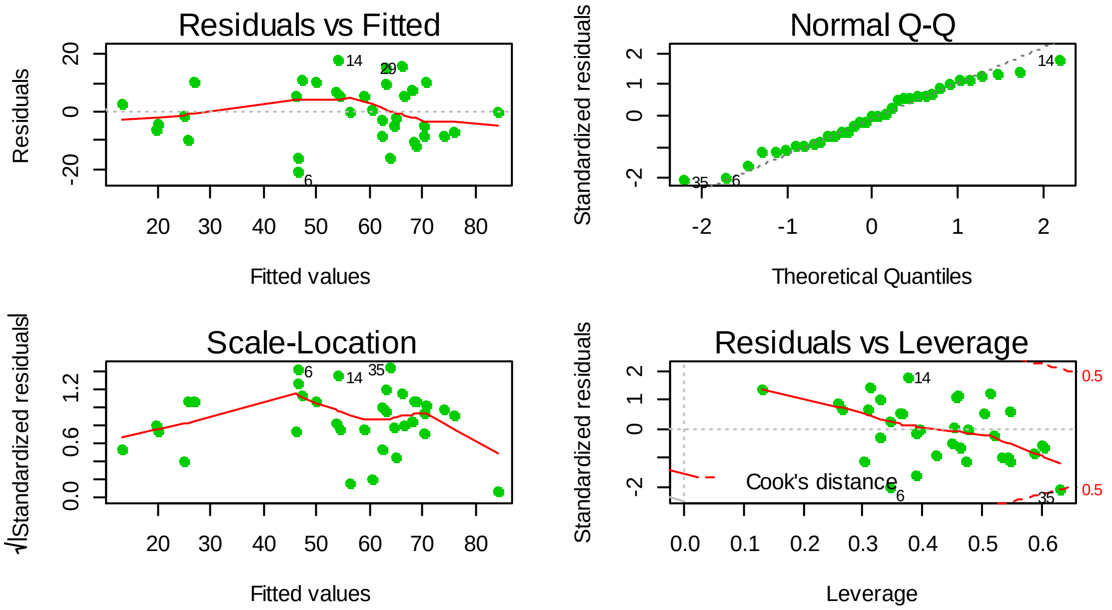

Figure 6: Residuals Diagonstics for Wheat Production Model

From Figure 6, we observe that,

1) all of the points are lied around the horizontal line and they try to create a horizontal band, which implies constant variance among the residuals of the wheat production model (top-left).
2) almost all of the points try to create a horizontal band which indicates that residals have constant variance of the wheat production model (bottom-left).
3) although there is a single leverage point, according to the cook's distance it is approximately on the 50% Cook's interval of the leverage points, which hhas small amount of influence on the model estimation of the wheat production model (bottom-right).
4) almost all of the points are very closed to Q-Q line or on the Q-Q line, which suggests that residuals are normally distributed of the wheat production model (top-right).

To check different assumptions by using formal test for multiple regression model of maize production are shown in the following Table 10

Table 10: Residuals Diagnostic test for Assumptions Checking

Residuals Diagnostic	**Test Name**	**P-value**
Constant Variance test	Breusch-Pagan	$\Pr(\lvert\chi^2_{(14)}\rvert \geq 8.1997\ ) = 0.8787$
Auto-correlation test	Box-Ljung test	$\Pr(\lvert\chi^2_{(1)}\rvert \geq 3.6274) = 0.1004$
Normality Test	Shapiro-Wilk	$\Pr(\lvert\chi^2_{(35)}\rvert \geq 0.9799) = 0.7553$

From Table 10, it is clear that residuals of the fitted Multiple Regression model for wheat production have constant variance, have no auto-correlation and they follow normal distribution at 5% level of significance which implies the fitted model's assumptions are very well managed. These all test are made based on Chi-square test.

8.5.2. Global Validation Checking for Maize Production Model

Global model validation test is used to check whether wheat production model assumption are valid or not. The test is performed at 5% level of significance on 4 degrees of freedom. The results from the test are shown in the Table 11.

Table 11: Global Validation Checking for Maize Production Model

Test Statistics	**Value**	**p-value**	**Decision**
Global Stat	2.89158	0.5761	Assumptions acceptable
Skewness	0.01992	0.8878	Assumptions acceptable.
Kurtosis	0.94304	0.3315	Assumptions acceptable.
Heteroscedasticity	0.18748	0.6650	Assumptions acceptable.

From Table 11, we observe that the p-value of Global stat is 0.5761, which suggests that linearity of parameters, Homoscedasticity, Autocorrelation and Normality test are very well managed in the fitted model, That is, the fitted model is a valid model. Again, Skewness and Kurtosis of the fitted model are 0.01992 and 0.94304 respectively and their corresponding p-values for testing hypothesis are 0.8878 and 0.3315, which suggest that the assumptions of the skewness and kurtosos are very well accepted to fit a linear model. At the same time, the heteroscedasticity assumptions is also accepted with the p-value of 0.6650, which suggests homoscedasticity of variance. We can easily say that the fitted model is the best fitted Multiple linear Regression model for measuring the climatic and hydrological effects on wheat production in Bangladesh.

Finally, from all of the test, assumptions of residuals like Homoscedasticity, Autocorrelation Normality are very well satisfied and model validation test “Global Tesst” also satisfied all of the assuptions of a linear model and the fitted model is a valid model. Without any kind of loss of generality, it can be said that this fitted model is the best fitted model for measuring the climatic effects on wheat production based on the sample data.

8.6. Stochastic Frontier Modeling for Wheat Production

Parameter estimates of the fitted stochastic frontier model of Trans-log Cobb-Douglas type for the wheat production are given in the Table 12.

Table 12: Summary statistics of the frontier model for Wheat productions model

Coefficients	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	115.234638	8.094453	14.2362	<0.0001
sun.sum	-13.082488	1.723501	-7.5906	<0.0001
sun.dry	-1.727133	1.242303	-1.3903	0.164448
clo.sum	-11.589615	2.300539	-5.0378	<0.0001
clo.dry	1.162891	0.711391	1.6347	0.10212
max.tem.dry	23.535306	4.547182	5.1758	<0.0001
max.tem.sum	-37.496213	3.576649	-10.4836	<0.0001
min.tem.dry	-12.771229	3.598432	-3.5491	0.000387
min.tem.sum	20.52626	4.10061	5.0057	<0.0001
rain.dry	-0.000896	0.192097	-0.0047	0.996278
rain.sum	-0.419963	0.725474	-0.5789	0.562669
rh.dry	0.266866	3.258775	0.0819	0.934733
rh.sum	-9.103338	3.561859	-2.5558	0.010595
wind.dry	0.001224	1.046729	0.0012	0.999067
wind.sum	-2.475561	1.127715	-2.1952	0.028149
sigmaSq	0.140945	0.033841	4.1649	<0.0001
gamma	0.000077	0.086527	0.0009	0.999286

From the Table 12 of the summary statistics, it is clear that sun.sum, clo.sum, clo.sum, max.tem.dry, max.tem.sum, min.tem.dry, min.tem.sum, rh.sum and wind.sum have statistically significant effects on frontier wheat production due to Climate and hydrology covering the whole Bangladesh at 5% level of significance.

From the calculated results, Average Technical Efficiency is 0.9973693. The highest value of the efficiency is 0.9973881, which occurs in the year 1985, that is, in the year 1985, Bangladesh achieves maximum wheat production and the lowest is 0.9973524, which occurs in the year 1978, that is, in the year 1978, that is, Bangladesh achieves minimum wheat production due to climates and hydrology. These result indicates that the majority of years are relatively well in achieving maximum wheat production due to climates and Hydrology. Efficiency rate approximately 100% gives sense that almost all of the year can achieve maximum wheat production due to climates and Hydrology. At the same time, according to the Coelli's test $H_0: \gamma = 0$, gives the value of gamma is 0.000077 and it's p-value for testing the hypothesis is 0.999286 indicates highly insignificant, which implies that all of the deviations arises due to stochastic noise. It also means that there is no opportunity to increase wheat production in the Bangladesh due to climates and hydrology. Again, from the likelihood ratio test, it is found that the $\Pr(|\chi^2_{(1)}| \geq 0) = 0.4996$, which implies to accept the null hypothesis that there is no production inefficiency, that is, there is no inefficiency of the wheat production in Bangladesh due to climate and hydrology.

9. Conclusion and Recommendations

The main objective of this study is to develop a Multiple Regression model to measure the climatic and hydrological effects on cereal crop productions in Bangladesh and Stochastic Frontier model for measuring the production efficiency due to climate and hydrology. To serve this purpose, we try to the Multiple Regression model and to check whether these model are valid or not, Global test is used. At the same time, to measure production efficiency due to climate and hydrology, Stochastic Frontier Model is used. We take the month October, November, December, January and February as a "**dry season**" and March, April, May, June, July, August, September as a **"summer season"** considering the weather and climatic conditions of Bangladesh. From the analysis, it is found that the Multiple R-squared values for maize, wheat and barley production models are 0.9447, 0.7674 and 0.7674, which are implied that 94.47%, 0.7674 and 76.74% variation can be explained by the regressor variables respectively. The value of R-squares are also implied to fit a good model to measure the Climatic and hydrological effects on different cereal production in Bangladesh. Again, from Global test, the p-values for maize, barley and wheat production model are 0.382, 0.1601 and 0.5761 respectively, which are implied that these models are valid linear model to make decision. Again, sun.dry, rh.dry and wind.sum have statistically significant effects on barley production. Similarly, sun.sum, sun.dry, clo.sum, clo.dry, max.tem.sum and wind.dry have statistically significant effects on maize production. At the same time, sun.sum and clo.sum have statistically significant effects on wheat production. Again, from the Stochastic Frontier model, Average Technical Efficiency of barley and maize productions are 0.7885847 and 0.4854803 respectively. They also mean that there is a huge opportunity to increase barley and maize production. Similarly, mean efficiency for wheat production model is 0.9973693, which implies that the majority of year are relatively well in achieving maximum wheat production due to climates and Hydrology in the Bangladesh.

After conducting this analysis the following recommendation can be made

- The policy makers and researchers can use these Multiple Regression model to make a decision for agricultural productions under consideration of climatic and hydrological effects on agricultural productions.
- The climatic zone similar to the Bangladesh can also use these Multiple Regression model.
- Stochastic Frontier Model can also be used to measure the production Efficiency in Bangladesh and policy makers try to make decision based on this.

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